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A Multi-factor Fuzzy Inference and Concept Map Approach for DevelopingDiagnostic and Adaptive Remedial LearningSystems

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Abstract

This paper proposes a method for evaluating learning achievementand providing personalized feedback of remedialsuggestion and instruction for learners. It functions as a combination of threeparticular processes.The first isbased on learners' test results to calculate the values of four diagnostic factors - accuracy rate, test difficulty, confidence level, and length of answer time. The second is to employfuzzy theory to infer learning achievement of learners. The thirdprovides personalized feedback for learners based on concept map with cognitive taxonomy. Experimental results reveal that the proposed method can help learners to learn more effectively and efficiently.

Keywords: Learning diagnosis; Fuzzy inference;Adaptive feedback; Concept map; Taxonomy of cognitive objectives

1. Introduction

To evaluate learning achievement of learners is an important research topic of adaptive learning systems.Providing students with evaluation reports regarding theirtest/examination as sufficiently as possible and with theunavoidable error as small as possible is the chief aim ofeducation institutions (Biswas, 1995). In recent years, researchers have proposed various approaches for developing adaptive learning systems based on the personal featuresor learning problems of learners(Hsu et al. 1998; Chen and Lin 2001; Hwang et al. 2008; Bai and Chen 2008a; Bai and Chen 2008b; Bai and Chen 2008c; Chen

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and Bai 2009; Lee et al. 2009; Lazarinis et al. 2010).Chen and Bai (2009) presented a methodconsideringthe learning degrees and accuracy rates for diagnosing thelearning barriers,it can overcome the drawbacks of the method presentedbyLee et al. (2009), and can more reasonably diagnose the learningbarriers foradaptive learning. However,in their study there are simply two factors taken in consideration for identifying the learningbarriers of learners. In addition to the learning degrees and accuracy rates, some researches argued that in order to evaluate more accuratelylearning achievement,educators must consider multiple criteria, such as the test difficulty, lucky guesses, and length of answer time(Petr 2000; Hameed 2011).

In Petr's method, students wereinstructed to"Indicate your confidence rating for eachanswer by circling a number from -5 (very confident it iswrong) to 5 (very confident it is correct)."A confidence score that measuredhow well the students evaluated the correctness orincorrectness of their answers canreflect theprobabilitya student gives the right answer due to lucky guess or not.Besides, the shorter time spent to answer a hard question correctlyimplies a stronger knowledge of the concept(Agarwal et al. 2006; Hameed 2011)Hence, this study not only employs theaccuracy rates, but also considers the test difficulty, lucky guesses, and length ofanswer time in theprocessing of learning achievement diagnosis, attempting to make thediagnosis morecompletely.

Since Zadeh (1965)proposed the concept of fuzzy set theory,it has been widely used in solving problems in various fields.Some methods have been reported for applying the fuzzy set theory in educational grading systems.According to the previous studies, the fuzzy set theory is proven to be an efficient and effective method to handle the uncertain and vague terms in an assessment environment(Biswas, 1995, Ma & Zhou, 2000, Wang&Chen, 2008, Saleh& Kim, 2009). Since the information of evaluating learning achievement is usuallyrather imprecise, uncertain and subjective, we consider fuzzy logic technique is suitable fordealing with thesekindsof vague situations. Therefore,in this paper the proposed system applies fuzzy set theory to provide expert-like reasoning ability which can infer the learning achievement for providing adaptive learning feedback to learners.

Novak (1998) proposed Concept Map to organize or represent the knowledge as anetwork consisting of nodes (points/vertices) as concepts and links (arcs/edges) as the relations among concepts.It has been proposed and applied invarious domains.Forexample,Hwang (2003)proposed aconceptual map model which provides learning suggestions by analyzing the subject materials and testresults.Tseng et al. (2007) proposed a Two-Phase Concept Map Construction (TP-CMC)approach to automatically construct the concept map by learners' historical test records.Although concept map has shown its effectiveness in helping learners tofind out their learning problem, it still lackssome information.In the existing concept map, itonlyprovides the information about the concept and their relationships, while the cognitive objective of each concept cannot be exhibited.Instead ofshowing that the learner will 'understand the concept', amore precise statement is that the learner will 'summarize the main rules from theinstructions to the concept'(Mayer 2002).Research and theory in Cognitive Science have shown that human cognition can be analyzed into Remember, Understand, Apply, Analyze, Evaluate, and Create in the order of complexity(Anderson et al. 2001). By using the taxonomy of cognitive objectives, educators can create a student-centered learning environment thatfosters a range of thinking skills, from the recall of factual information to thedevelopment of critical thinking and problem solving skills(Gronlund 2004). Therefore,it is meaningful to incorporatecognitive objectives with concept map. After evaluating the learning achievement, the diagnosis report of learning barriers should be provided according to the concept map with cognitive objectives to offer more information than the traditional one.

The purpose of this studyisillustrated as follows. First, multiple factors are taken into consideration to provide more flexible and completediagnosis.Next, we explore fuzzy logic as human thinking and judgment for assessinglearners' learning achievement. Finally, according to the diagnosis, the adaptive feedback of remedialsuggestion and instruction are provided tolearners.The rest of this paper is divided into four sections. Section 2describes the mechanism for diagnosing learner's learning achievement and the adaptive feedback for learners. Section 3 introduces the implementation of the proposed method.

Section 4 presentsan experiment to evaluate the performanceof the proposed method. Finally,the conclusions are drawn in Section 5.

2. Methodology

The proposed learning diagnosis mechanismuses multi-factor fuzzy inferenceand concept map to evaluate learners' learning achievement and generate adaptive feedback and remedial instruction for learners.First,the diagnostic factors are illustrated in Section 2.1. Second,using fuzzy inference to diagnose learning achievement is stated in Section 2.2. Finally, the personalized feedback of remedialsuggestion and instruction based on concept map with cognitive taxonomy is depicted in Section 2.3.

2.1. Diagnostic factors

As stated above, four diagnostic factors are considered in this study for determining learning achievement: accuracy rate of concept, test difficulty, confidence level (for measuring the lucky guess), and length of answer time. There arethree sourcesutilized to acquire the data of diagnostic factors:testing information assigned by instructors, testing results derivedfrom learners, and relationshipsamong concepts. When selecting a questionfor testing, the general principle to follow is to ensure the questionshould be related to a specific concept so that acorrect answer implies the possession of knowledge of thatconcept(Agarwal et al. 2006).Based on the principle,this study assigns a specific concept to each question asshown in Table 1, where$Q_tC_i = 1$represents 'relevant' and $Q_tC_i = 0$represents 'irrelevant',$1 \le t \le m$, and $1 \le i \le p$. Besides, in order to identify how strongly a correct answer impliesconcept mastery. Eachquestion$Q_t$should be related to adifficult degreeD_t as shown in Table 2, where $0 \le D_t \le 1$and $1 \le t \le m$.After the initial setting of questions, the instructor performs a test to record the answers of the learners. The relationshipR_{tj}between question$Q_t$and learner $S_j$isshown in Table 3, where $R_{tj} = 1$ indicates that learnerS_j answered questionQ_t correctly; $R_{tj} = 0$ indicates that learnerS_j failed to answer questionQ_t correctly, $1 \le t \le m$, and $1 \le j \le n$.

Table 1.Associationsbetween questions and concepts

Questions	Concepts				
	C_1	C_2	C_3	...	C_p
Q_1	Q_1C_1	Q_1C_2	Q_1C_3	…	Q_1C_p
Q_2	Q_2C_1	Q_2C_2	Q_2C_3	…	Q_2C_p
...	…	…	…	…	…
Q_m	Q_mC_1	Q_mC_2	Q_mC_3	…	Q_mC_p

Table 2.Difficulty degree of eachquestion

Questions	Q_1	Q_2	Q_3	...	Q_m
Difficulty Degree	D_1	D_2	D_3	...	D_m

Table 3. Associationsbetweenlearner's answers and questions

Questions	Learners				
	S_1	S_2	S_3	...	S_n
Q_1	R_{11}	R_{12}	R_{13}	...	R_{1n}
Q_2	R_{21}	R_{22}	R_{23}	...	R_{2n}
...	...	...	...	...	...
Q_m	R_{m1}	R_{m2}	R_{m3}	...	R_{mn}

Regarding the accuracy rate, fromthe conceptual relationships in test questions shown in Table 1 and theanswer record of learners shown in Table 3, the accuracy rateac_{ij} of the learnerS_j with respect to the concept C_i can becalculated by Formula (1) which is the same asused by (Chen and Bai 2009):

$$ac_{ij} = \frac{\sum_{t=1}^{m}(R_{tj} \times Q_tC_i)}{\sum_{t=1}^{m} Q_tC_i} \times 100\% \qquad (1)$$

where R_{tj} denotes the record of the learner S_j with respect to thequestionQ_t, $Q_tC_i$denotesthe relationships of the concept C_i in the question Q_t,$1 \leq j \leq n$, $1 \leq t \leq m$, and $1 \leq i \leq p$.

Regarding the test difficulty, fromthe conceptual relationships in test questions shown in Table 1 and thedifficulty degree ofeach question shown in Table 2, the averagedifficultydegree D_{ij} of concept$C_i$answered correctly by learner $S_j$can becalculated by Formula (2):

$$D_{ij} = \frac{\sum_{t=1}^{m}(R_{tj} \times Q_tC_i \times D_t)}{\sum_{t=1}^{m} Q_tC_i} \times 100\% \qquad (2)$$

where R_{tj} denotes the record of the learner S_j with respect to the question Q_t , Q_tC_i denotes the relationships of the concept C_i in the question Q_t , and D_t denotes the difficulty degree of each question,$1 \leq j \leq n$, $1 \leq t \leq m$, and $1 \leq i \leq p$.

Table 4. Relationships between concepts

Concept	Concepts				
	C_1	C_2	C_3	…	C_p
C_1	W_{11}	W_{12}	W_{13}	…	W_{1p}
C_2	W_{21}	W_{22}	W_{23}	…	W_{2p}
…	…	…	…	…	…
C_p	W_{p1}	W_{p2}	W_{p3}	…	W_{pp}

In the adaptivelearning environment, the Concept Map can be used to demonstrate how the learning status of aconcept can possibly be influenced by the learning status of other concepts(Tseng et al. 2007). In addition, there exist the prerequisite relationships among concepts, so each concept needs to be learned ina dedicated order(Hwang 2003).Regarding thelucky guess influence, weuse the prerequisite relationshipsamongconcepts to calculate the confidence level of each concept for learners.Confidence level can be defined as the degreethat the learner has understood the concept, and it can be used to judge the probabilitythat the learner correctly answered the questions related to a concept due to lucky guesses.Table 4 shows the relationships among concepts, where W_{xy} indicates the prerequisite relationship between the concept C_x and conceptC_y, and $C_x$is the prior knowledge of C_y where$0 \leq W_{xy} \leq 1$.Let $C_x$be the prior knowledge ofC_y, and $C_y$be the prior knowledge ofC_z.If a learnerS_j correctlyanswered the questionswith respect to the concept$C_y$or C_z, then the confidence level of the learnerS_j with respect to conceptC_y will be increased. If a learner $S_j$wronglyanswered the questionswith respect to the conceptC_x, then the confidence level of the learnerS_j with respect to conceptC_y will be decreased. And the increased and decreased value is proportional tothe prerequisite relationship between two concepts andthe difficulty degree of each question. Hence,the confidence level of the learnerS_j with respect to each concept can be calculated by Formula (3)

$$CL_{ij} = \frac{\sum_{k=1}^{p}\sum_{t=1}^{m} Q_tC_k \times W_{ik} \times D_t \times R_{tj} + \sum_{t=1}^{m}\left(\sum_{k=1}^{i-1} Q_tC_k \times W_{ki} \times D_t \times (R_{tj}-1) + \sum_{k=1}^{i+1} Q_tC_k \times W_{ki} \times D_t \times (R_{tj}-1)\right)}{\sum_{k=1}^{p}\sum_{t=1}^{m} Q_tC_k \times W_{ik} \times D_t} \times 100\% \qquad (3)$$

where CL_{ij} denotes the confidence level ofthe learnerS_j with respect to concept C_i, W_{ki} denotes the prerequisiterelationship between the concept C_k and conceptC_i ,R_{tj} denotes the record of the learner $S_j$with respect to the question Q_t, Q_tC_i denotes the relationships of the concept C_i in the question Q_t, and$D_t$denotesthe difficulty degree of eachquestionQ_t, $1 \leq j \leq n$, $1 \leq t \leq m$, and $1 \leq i, k \leq p$.

2.2. Diagnosis based on fuzzy inference

To usefullydeal with imprecise information and obtain more precise estimation of the learning achievement of learners, the technique of fuzzy inference is employed.The processis detailed as follows.The input variables of fuzzy inference mechanism are accuracy rate, test difficulty, confidencelevel and length of answer time.Among these input variables, the accuracy rate, test difficulty and confidencelevel can be calculated by Formula(1)-(3), while the length of answer time is the total time spending to solve the test by a learner.To present the linguistic variables of input and output for the fuzzy inference mechanism, five trapezoidal membership functions are defined by experts as shown in Fig. 1. Thetrapezoidal membership function is defined as Formula (4)(Lee and Wang 2008). Then, the fuzzy inference mechanism performsmembership functions tocompute the membership degreesfor each fuzzy input variable.

$$FS(x: p1, p2, p3, p4) = \begin{cases} 0, & x < p1 \\ (x - p1)/(p2 - p1), & p1 \leq x \leq p2 \\ 1, & p2 \leq x \leq p3 \\ (p4 - x)/(p4 - p3), & p3 \leq x \leq p4 \\ 0, & x > p4 \end{cases} \quad (4)$$

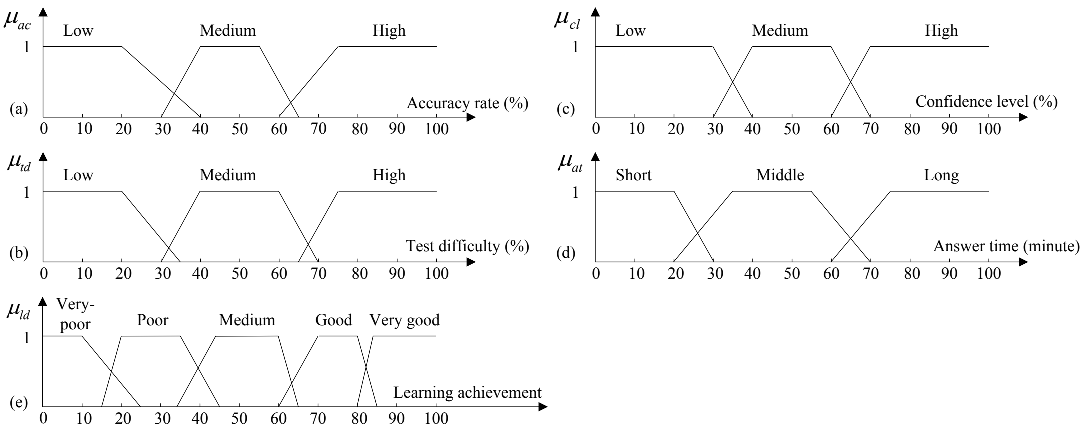


Fig. 1.The membership functions for fuzzy variables(a) Accuracy rate; (b) Test difficulty; (c) Confidence level; (d) Answer time; (e)Learning achievement

Table 5.Part of theconstructed fuzzy rules

Rule no.	Input fuzzy variables				Output fuzzy variables
	Accuracy rate	test difficulty	confidence level	answer time	learning achievement
R1	Low	Low	Low	Short	Very Poor
R2	Low	Low	Low	Middle	Very Poor
R3	Low	Low	Low	Long	Very Poor
…	…	…	…	…	…
R80	High	High	High	Middle	Very Good
R81	High	High	High	Long	Very Good

Furthermore, this studyemploys 81 fuzzy rulescorresponding to allpossible combinations of input terms.The ideas behind the construction of thefuzzy rules are stated as follows.The better thelearning achievement is(1) the higher the accuracy rate, test difficulty, and confidence level are; as well as (2) the faster the answer time is.Hence, theexperts constructed the fuzzy rulesaccording to these criteria and Table 5 lists part of theconstructed fuzzy rules.TheMamdani'sminimum implication(Zimmermann 1987)is then used to integrate triggered rules with the same consequences.Finally, the defuzzification method of center of gravity is used to acquire the crisp value to represent learner's learning achievement.

2.3. Personalizedfeedbackbased on concept map with cognitive taxonomy

In order to help learners learn more effectively and efficiently,a well learning diagnosis system shouldnot only diagnose the learningachievement and barriers, but also providepersonalized feedback of remedialsuggestion and instruction.

Concept Map has been widely adopted for assessing learning barriers of each concept, thus this study provides the diagnosis of each concept for learners. Additionally, research and theory in cognitive science have shownthat human cognition can beanalyzed intoRemember, Understand, Apply, Analyze, Evaluate, and Create in the order of complexity.In order to provide learners with more learning information, in this study each concept is related to one or more particular cognitive levels, as shown in Fig. 2(a).Besides, each question isalso related to a specific cognitive level, as show in Fig.2(b).Different question types may be suitable for judging different cognitive levels, such as True-False, Multiple-ChoiceandMatchingaresuitable for judging the Remember level, Understand level, andApply level.Essayis suitable for judging theAnalyze level, Evaluate level, and Create level.When a learner fails in some concept, it indicated that there is a learning barrier for this learner, and the learner can remedy this concept by enhancing theparticular cognitive level of this concept. Hence, the suggestions provided by this study for learners are not only to understand the learning achievement of each concept, but also to help them understandtheircognitive level about each concept and constructive process of knowledge acquisition.

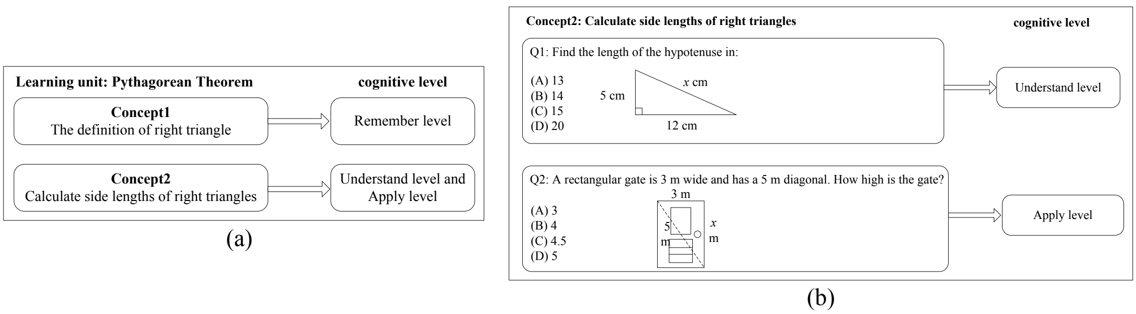


Fig. 2.Example of concepts and questions related to specific cognitive levels(a)Concepts related to specific cognitive levels; (b) Questions related tospecific cognitive levels

To verify the validity of the proposed learning achievement diagnosismechanism and effectiveness of the personalized feedback of remedialsuggestion and instruction,this study also includes the development and evaluation of a diagnostic and adaptive remediallearning systemwith theadaptive remedial learning materials for learners.

3. System development

Based on the proposed approach, aweb-based Intelligent Diagnosis and Adaptive Remedial (IDAR) learning system has been implemented using PHP and MySQL. IDAR comprises two major modules,one is for the fuzzy-based diagnosis to evaluate learner's learning achievement, and the other is for the adaptivefeedback of remedial suggestion and instruction. The architectureof IDAR is depicted in Fig.3.

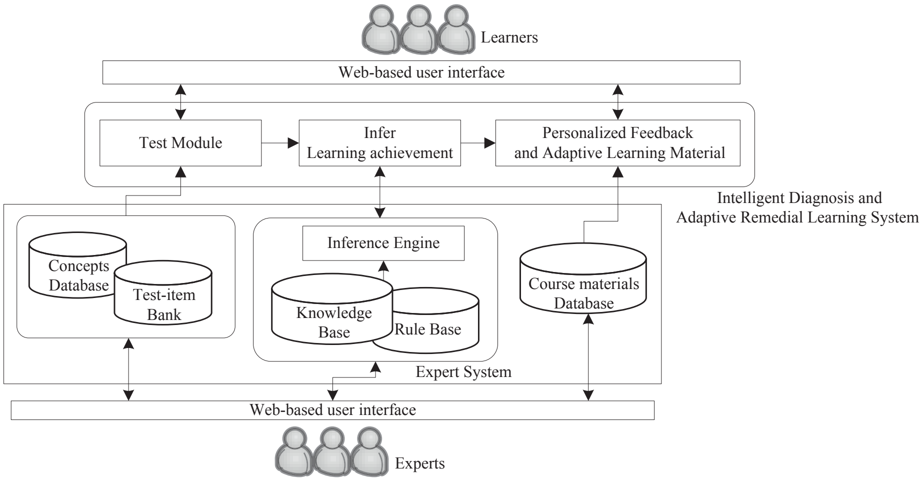
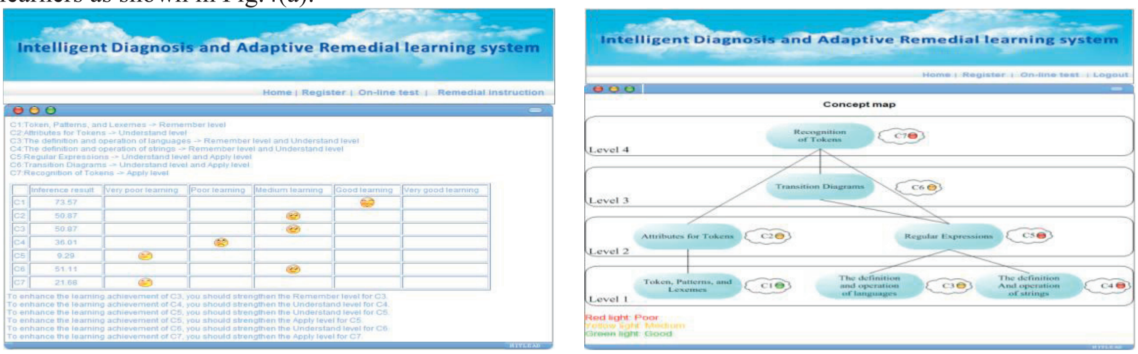


Fig. 3. The architecture of the intelligent diagnosis and adaptive remedial learning system

In the beginning,the experts design testing items and determine the difficulty level of each test item and theirrelationships between concept and test item,which are stored in the test item bank. In this study, the test item types contain True-False and Multiple-Choice which is suitable for judging the Remember level, Understand level, andApply level. Besides, the relationship between two concepts is determined by the experts and stored in the concept database. After the learner finish the test, the inference engine uses predefined knowledge base and rule base to infer the learner's learning achievement based on their test results.An example of inference result and the inferiorcognitive levels of each concept are provided to the learners as shown in Fig.4(a).



(a) (b)

Fig. 4.Example ofsystem interface (a)inference result and personalized feedback; (b) personalized remedial instruction

Moreover, this system offers a personalized remedial learning environment for learners to strengthen theirunderstanding of each concept. Fig.4(b) shows an example of concept map which is a clickable image map. When learners click on one of the concept node, they're directed to the page which presents adaptive learning materials according to their diagnostic results. And the learners of Fig.4(b) should learn the concepts from level 1 to level 4.

4. Evaluation and analysis

4.1. Experiment design

We conducted an experiment involving fifty-two students enrolled in a course of compiler construction at a university in Taiwan. The students were grouped into a control group and an experimental group according to their average quiz score of the course, so that their compiler background knowledge were more or less balanced.

(1) Control group: In this group, 25 students used the system diagnosing learning barriers based on the accuracy rate of each concept and providing personalized learning guidance for them. The learning materialswhich students studied are textbook and their notes.

(2) Experimental group: In this group, 27 students used the IDAR system diagnosing learning achievement based on fuzzy theory and providing personalized suggestions and adaptive learning materials for them.

4.2. Analysis of pre-test and post-test

First, all of the students took a pre-test to evaluate whether they had the same knowledge level with regard to learning compiler. Then, according to the learning suggestions, all of the students strengthentheir understanding of each concept. After finishing the remedial learning activity, all of the students took a post-test.In the following, an independent-samples t-test was adopted to analyze the experiment results as shown in Table 6, it is obvious that there is no significant ($p > 0.05$) difference between Experimental group and Control group in the pre-test, but significant ($p < 0.05$) difference between Experimental group and Control group in the post-test.

Table 6.Theindependent-samplest-Test results of the pre-test and post-test results

Tests	Group	N	Mean	S.D.	T	P
Pre-test	Experimental	27	22.74	7.27	-1.129	0.264
	Control	25	24.92	6.58		
Post-test	Experimental	27	33.88	9.78	2.013	0.049*
	Control	25	29.0	7.46		

*p<.05.

Table 7. The paired t-Test results of learning improvement for the two groups

Group	Tests	N	Mean	S.D.	T	P
Experimental	Pre-test	27	22.74	7.27	-4.681	0.000**
	Post-test	27	33.88	9.78		
Control	Pre-test	25	24.92	6.58	-2.303	0.030*
	Post-test	25	29.0	7.46		

*p<.05.**p<.001.

A paired t-test was then used to analyze the learning improvement for these groups, as shown in Table 7, and the results reveal that both of these two systems could help students to improve their learning performance. However, Table 6reveals that the IDAR system is more useful than the other one in improving the learning achievement of learners.

5. Conclusions

This study proposed a novel approach relying on fuzzy inference and concept map, which can diagnose learner's learning achievementand provide adaptive remedial suggestion and instruction. To obtain more accurate diagnostic results, the proposed method considers accuracy rate, test difficulty, confidence level (for measuring the lucky guess), andlength of answer time as the diagnostic factors.Besides, by incorporating cognitive objectives with concept map,more complete learning suggestions can be provided to each learner. An experiment has been conducted to evaluate the efficacy of the novel approach.The experimental results show that the proposed methodcansignificantly help learners improve their learning performance. It implies that the proposed method is effective in evaluating and improvinglearners' learning achievement.

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